# A STATISTICAL ANALYSIS OF INDUCED TRAVEL EFFECTS IN THE U.S. MID-ATLANTIC REGION


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**Abstract**

The hypothesis of induced travel demand is investigated. County level data from Maryland, Virginia, North Carolina, and Washington, DC is used to estimate “fixed effects” cross-sectional time-series models that relate travel levels (measured as daily vehicle miles of travel) to roadway capacity (in lane miles). This includes analysis of a difference (or growth) model estimated using a two stage least squares procedure with an instrumental variable to account for simultaneity bias. Individual models for each state, a combined-state model, and a model with data from the Washington, DC / Baltimore metropolitan area are estimated. Results are generally significant and relationships are robust across geographic areas and different specifications. Average elasticities of VMT with respect to lane miles are estimated to be on the order of 0.2 to 0.6. A Granger Causality test indicates that growth in lane miles precedes growth in VMT. Overall, the results build on other recent research in this area by both confirming the range of elasticities found in other studies and confirming the robustness of these estimates by accounting for simultaneity bias.

## Introduction

Recent work has empirically estimated relationships between lane miles of highway capacity and vehicle miles of travel (VMT). Hansen & Huang (1997) estimated elasticities of VMT with respect to lane miles using data on California counties and metropolitan areas. Noland (forthcoming) estimated nationwide relationships with state level data using a similar approach. Noland & Cowart (2000) also have developed estimates using a database of metropolitan areas. This paper extends this work by estimating models similar to those of Hansen & Huang (1997) using county level data for the Mid-Atlantic region of the country, the states of Maryland, Virginia, and North Carolina and also a separate analysis for the Washington, DC / Baltimore metropolitan area. It also extends previous work by estimating an instrumental variable model using two stage least squares estimation to account for simultaneity bias in the data. Noland & Cowart (2000) also tested possible instrumental variables but with mixed results given the weakness of the instruments they selected. The analysis presented here provides strong support for the causal nature of the relationship between new highway capacity and increases in VMT.

Recent literature on the relationship between roadway capacity and levels of vehicle travel appears to be building a consensus on general effects despite the lack of an explicit accounting for simultaneity bias. Short run elasticities (based upon changes in travel with respect to changes in roadway capacity) of VMT with respect to lane miles have commonly been found to be on the order of 0.2-0.6 with long run elasticities of 0.6-1.0. This research shows results within the lower bound of previous work that has used aggregate data and econometric techniques.

Other literature has been based on observational traffic counts within travel corridors. These studies have generally not accounted for other exogenous effects that could also contribute to growth in VMT that econometric techniques have accounted for either explicitly or through the use of fixed effects models (see Transportation Research Board, 1995, for a good review of research dating back to the 1940's). More recently in a comprehensive study that utilized traffic count data, Goodwin (1996) controlled for exogenous factors that affect VMT growth by selecting comparable control corridors. In general, he finds significant increases in traffic due to specific highway improvement projects within these corridors and estimates travel time elasticities of -0.5 to -1.0. Overall the results of recent econometric studies provide similar coefficient values to those derived in the work presented here.

The following section provides a discussion of the phenomenon known as induced travel demand, and how this analysis addresses the questions surrounding the issue. This is followed by a description of the database and methodology used in the analysis. This is followed by the results with interpretation of the econometric analysis. A concluding section discusses policy implications and how this could affect the planning of road facilities.

**Induced Demand: The Issue and Underlying Economic Theory**

The concept of "induced demand" involves the idea that additions to roadway capacity result in, or induce, increases in vehicle travel on the roadway (and the network) above the level that occurred before the capacity addition. Whether, and to what extent, addition of roadway capacity "induces" additional travel has been a cause of controversy in recent years and is confounded by the fact that other exogenous factors such as increases in population and demographic changes have also been drivers of VMT growth. Planners have historically considered transportation demand as a derived demand for economic activities and assume that travelers will change their behavior as their desire to engage in alternative activities changes over time. This leads to the assertion that capacity increases (including increases in transit capacity) will be effective at reducing congestion and are needed to account for exogenous growth in travel. An understanding of the basic economics of induced travel challenges this argument and recognizes that individuals will make both travel and location decisions in response to the generalized cost of travel.

The basic theory underlying the concept of induced travel demand is straightforward. The addition of roadway capacity, either through additional miles of roadway or additional lanes on an existing roadway, reduces the time cost of travel. At some level of congestion, any given driver will choose to avoid dealing with that congestion, either in favor of an alternative route, an alternative mode, changing the departure time of the trip, a shorter trip to a similar activity, or avoiding the trip entirely. Hills (1996) outlines and describes these behavioral effects.

The aggregate impact on VMT of these behavioral effects is shown in Figure 1. Since each traveler experiences declining utility with each mile traveled, at some point the cost of travel exceeds the benefit to the driver. This increase in generalized cost is primarily the time cost associated with increasing congestion. This is shown as point "a" in the figure. If, however, congestion is relieved through the addition of roadway capacity, the entire cost curve shifts outward (reflecting a shift toward lower travel time cost). This allows higher aggregate levels of travel before a given level of congestion is reached. The effect is shown in the figure as a shift of the time cost curve and a movement of the equilibrium point along the demand curve from point *a* to point *b*. A reduction in time cost from point *p* to *p'* yields an increase in travel from point *q* to *q'*. In addition, long term responses to increased access can result in changes in land use patterns that may induce both more trips and longer trips.

These issues have been hotly debated in the transport literature for many years. Goodwin (1996) cites evidence for this effect in studies dating back to the 1930's. A special report of the Transportation Research Board (1995) assessed the impacts of expanding metropolitan highway capacity on air quality and energy use. While the basic theory of induced travel is extensively outlined and described in the text of the report, the conclusions (and a strong dissenting opinion by one member of the review committee) tended to indicate a lack of consensus on the overall theory. The focus of the report on air quality and energy consumption may have confused the issue somewhat as air quality and energy consumption changes due to changes in the dynamics of traffic flow (associated with capacity increases) are difficult to measure and model.

While the underlying economic relationships of induced travel are conceptually straightforward, there are at least two controversies surrounding the implications for roadway capacity expansion. The first is the specific nature of the relationship between capacity expansion and "induced" increases in travel. The second is whether the existence of this relationship indicates that roadway capacity expansion provides, on net, costs or benefits to society. This analysis focuses on the first of these questions.

While this study does not directly address the second issue, it should be noted that the size and nature of the effect has important implications for whether capacity expansion provides net benefits to society. A large induced travel effect indicates that many of the travel time reduction benefits of highway expansion may be lost to increased traffic volume (over whatever time period the elasticity applies). On the other hand, it could also suggest that there was considerable "pent up" travel demand that was released when the cost of driving was lowered and this could be interpreted as providing a benefit of increased mobility. Conversely, a small induced travel effect would indicate that most congestion benefits from capacity expansion are retained, and also that there is no significant latent travel demand going unfilled. The timing of the effects is also important. Long-run elasticities that are significantly greater than short run elasticities suggest that initial congestion reduction benefits may ultimately pave the way for increased development and other activities that lead to increased travel levels. While short run congestion reduction benefits may accrue to existing travelers, long run benefits may accrue to both new travelers and to the owners of land that is now more accessible. Cost / benefit analysis of these type of economic interactions are far more complicated to derive than a simple elasticity relationship, but ultimately such considerations are critical to assessing the impact of highway projects. The environmental implications of alternative development patterns that could be triggered by roadway capacity expansion is also an important issue and one that could determine whether a specific project provides, on net, costs or benefits to society.

**Data and Preliminary Analysis**

Following the approaches of Hansen and Huang (1997) and Noland (forthcoming) this study econometrically estimates the relationship between roadway capacity, measured as lane miles, and vehicle travel, measured as average daily vehicle miles of travel at the county level. Other key factors that influence travel are also controlled for. The extent of highway travel in an area is a function of many factors, including population, income, car ownership levels, land use, fuel prices (and other variable costs of travel), and availability of alternative modes of travel, such as transit. Any attempt to estimate the impact of additions to roadway capacity on travel levels should account for as many of these factors as possible.

The database for this analysis was originally developed by Energy and Environmental analysis and is fully documented in EEA (1999). It includes county level data for Maryland, Virginia, and North

Carolina as well as for the District of Columbia. Virginia does not incorporate a number of its cities into county jurisdictions; data for these cities was unavailable. Many counties in Virginia are highly urbanized and would be cities in other states, thus this is more of a definitional omission than a real data problem. Some of the cities may contain older, more established neighborhoods that have not had large increases in lane miles (relative to newly developed areas). The Maryland data excludes Baltimore City for which data was not readily available.[1]

For each county in each state, the data collected included geographic area, population and population density, income per capita, employment (available as total employment and unemployment rate), and extent of roadway lane miles in different roadway categories. The time series of lane mileage and VMT data varied by state. Virginia and Maryland had data available back to 1970 and 1969, respectively, while data for North Carolina and the District of Columbia extended back to 1985 and 1984, respectively.

The VMT and lane mile data that states submit to the Federal Highway Administration (FHWA) for use in the Highway Performance Monitoring System were not available (and in most cases are not kept) on a county-by-county basis. Nevertheless, each of the three states collects and tracks this data at a county level. In most cases, however, the data does not cover all roads or travel within each county, and so the state totals do not match the summary statistics for each state produced by the FHWA. In particular, each of these states only collect data on travel and roadway extent for roads that are state-maintained. In each of the states included in the analysis, this included all interstate lane miles, all state highways, and many (but not all) other primary roads. Data covering some secondary roads

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[1] Data for Baltimore City, which is separate from Baltimore County, is collected and maintained by the

was obtained for Maryland and North Carolina but not for Virginia. To maintain consistency, the database used in the analysis contains no secondary road data. There may be some data variation in the percent of roadway coverage in each state. This is not believed to represent a problem since the primary need is to have the data for VMT match the data for lane miles with respect to road coverage, which it does.

It should also be noted that the general method of VMT data collection appears to be similar in the three states, although there are some minor differences. In each case, the states collect VMT data primarily through traffic counts on a sample of roadway segments. Each state has a large number of portable "periodic" traffic counting devices, and these are placed on different roadway segments for several days at a time throughout the year in order to obtain the counts. Each state also has some dedicated "continuous" counters that are kept permanently in one location, but generally far fewer of these than portable counters used for sampling. A special effort is often, but not always, made to collect data on segments that are being considered for or recently had changes in capacity. VMT samples are aggregated to estimates of total VMT using a fairly standard methodology, involving the development of growth factors for each roadway link, based on VMT changes from previous years' sampling data. Although the basic approach to data collection appears similar in each state, the number of traffic counters and the frequency of sampling each roadway segment varies across the states. This is, then, a source of uncertainty in the accuracy and consistency of the VMT data used in the analysis. For this reason, we chose to estimate separate regression models for each state as well as models including all states together.

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city rather than by the State of Maryland. Historical data were not available from the City.

There are several variables that could be important but were unavailable for this analysis. As discussed in the methodology section below, the effects of these variables are captured by county-specific and year-specific intercept terms when utilizing a fixed-effects econometric specification. Average vehicles per driver by county may have been an important factor determining travel growth over the period but was unavailable for this study. However, it is likely to be highly correlated with the level of population. Fuel prices, although potentially important, were not easily available on a county level, only on a state level. Use of state level data would result in all counties within a state having the same fuel prices for a given year. The effects of this variable are therefore captured in any regression model including an intercept term for each year of data. Finally, transit data was not available for many counties so it is not included in the analysis. It has been noted by other analysts (e.g., Hansen and Huang, 1997) that the availability of transit itself may be influenced by roadway supply and may represent a joint product with highway travel, in which case controlling for it would be inappropriate.

Basic characteristics of the five study areas (and all areas taken together) are shown in Table 1. Several important differences can be seen across the different study areas. While the average geographic area of counties in each study area is quite similar, the average population (and therefore population density) varies considerably. The Washington, DC / Baltimore metropolitan area has about 1,600 persons per square mile, Maryland has about 420 per square mile, Virginia has slightly under 200 per square mile, and North Carolina has less than 150 per square mile. The travel per capita is inversely correlated with population density, with Virginia showing 30 percent to 40 percent more daily travel per capita (on interstates and state-maintained primary roads) than North Carolina and Maryland, with the Washington DC / Baltimore metropolitan area about ten percent below Maryland. This suggests that the more densely populated areas require fewer and/or shorter car trips, which may be due to proximity of destinations and/or greater availability of alternative (non-auto) travel modes.

The average number of lane miles per capita is also greater in the areas with lower population density, with a higher average in North Carolina and Virginia than in the Washington, DC / Baltimore metropolitan area and Maryland. This may reflect the presence of underutilized interstates and major arterials that have been put in place to provide access to the scattered populous of the rural counties in states such as North Carolina. It also may help explain why VMT per capita in densely populated areas is lower – the availability of roadway miles per person is much lower. If true, this would imply that congested conditions limit the VMT of residents in such an area to levels below areas with more roadway capacity available. These relationships are examined more formally in the following section using a multivariate analysis. Finally, the average daily travel (VMT) per lane mile of available roadway is indeed much higher in the more densely populated areas, again indicating that there is much less available road capacity in the Washington, DC / Baltimore metropolitan area than in Virginia, with North Carolina and Maryland intermediate.

Table 2 lists average annual growth rates of key variables. The growth rates for several key variables are significantly different across the different areas. While the growth rate in VMT is between 3% and 4% per year in all areas, the growth rate in lane miles varies significantly, ranging from 0.38% in Maryland to 0.87% in the Washington, DC / Baltimore area. In North Carolina VMT growth is larger than growth in either population or lane miles, suggesting that average travel per person has increased significantly. However, the average VMT per lane mile in North Carolina counties in 1995 (shown in Table 2) was still quite low compared to Virginia, Maryland, and the Washington, DC / Baltimore area.

Clearly, the rapid growth in travel per person in North Carolina has not (yet) resulted in roadway usage levels on a par with the other areas.

**Methodology**

In all estimated models, a "fixed effects" specification approach has been used. Fixed effects models use cross sectional and/or time series intercepts for each unit of observation. This technique has two primary advantages. First, it allows the analyst to use a larger data set (over time) rather than a simple one year cross-section of data. Second, the fixed effect terms, entered as intercept (or "dummy") variables for the cross-sectional units (one for each county) and for time (one for each year), capture the influence of factors unknown or unmeasured by the analyst (Johnston & DiNardo, 1997). Econometrically, a "fixed effects" model acknowledges the researcher's lack of information about the unique characteristics of each unit in the data. It can also reduce the bias associated with correlations across units that would normally be captured in the error term. The closer the error term is to being normally identically distributed, the less bias will be present in the standard errors of the estimates – in this case the relationship between lane miles and VMT. Since the data base used here is a panel data base, our fixed effects models also account for variations across time that might be correlated in the error term for individual counties. The fixed effects model is thus specified with a separate intercept term for each county and each year of data and is estimated using ordinary least squares regression. For a more detailed discussion of the fixed effects specification see, for example, Kennedy (1992) and Johnston & DiNardo (1997).

A logarithmic specification of the fixed effects model can be written as:

$$\log(VMT_{it}) = c + \boldsymbol{a}_i + \boldsymbol{b}_t + \sum_k \boldsymbol{l}^k \log(\mathrm{X}_{it}^k) + \boldsymbol{e}_{it}$$

where:

$VMT_{it}$ is the daily vehicle miles of travel for county i in year t;

$\boldsymbol{a}_i$ is the fixed effect for county i, estimated in the analysis;

$\boldsymbol{b}_t$ is the fixed effect for year t, estimated in the analysis;

$c$ constant term;

$X_{it}^{k}$ is the value of explanatory variable k for county i and year t; one component of which is lane miles (LM).

$\boldsymbol{l}^k$ is each of the set of K coefficients to be estimated;

$\boldsymbol{e}_{it}$ is the outcome of a random variable for county i in year t, assumed to be normally distributed with mean 0.

The model is specified with the natural log of the variables to avoid heteroskedasticity and to allow the estimated coefficients to be read as elasticities.

The issue of simultaneity bias is not explicitly addressed by this model formulation. Given that lane miles may be a function of forecasted growth in VMT, it is likely that this simultaneous relationship may result in an upward bias in the coefficient estimates. To both assess the importance of this effect and to adjust for it, several additional models are estimated.

A difference (or growth) model is analyzed first. This model essentially correlates annual growth in lane miles with annual growth in VMT. It has the added feature of eliminating much of the collinearity between independent variables. The specification of this model is as follows:

$$\log\left(VMT_{it}\right) - \log\left(VMT_{i(t-1)}\right) = c + a_{i} + b_{t} + \sum_{k} l^{k}\left(\log\left(X_{it}^{k}\right) - \log\left(X_{i(t-1)}^{k}\right)\right) + e_{it}$$

with variables as defined above.

This model is used as the basis for both a Granger causality test which examines the precedence of the variables. That is, does lane mile growth precede VMT growth or is the reverse true?

A two stage least squares estimate using the lagged growth in lane miles as an instrument for current growth in lane miles is formulated as,

$$\log\left(LM_{it}\right) - \log\left(LM_{i(t-1)}\right) = c + a_{i} + b_{t} + \sum_{k} l^{k}\left(\log\left(LM_{it)}^{k}\right) - \log\left(LM_{i(t-l))}^{k}\right)\right) + e_{it}$$

where the lag term, *l*, is equal to 2 or 3 in the estimates that follow. As will be seen this model provides a strong correlation between the growth in lane miles in the current year and the lagged growth in lane miles over multiple years. The instruments are not correlated with current growth in VMT. The difference specification is also used to avoid strong correlations in the independent variables that could create bias in some of the estimates.

**Results of Econometric Analyses**

Various econometric models were estimated using VMT as the dependent variable and lane miles, population, and income per capita as potential explanatory variables. Although the principal results are reported here, additional specifications are reported in EEA (1999). Separate regressions were analyzed for five geographic areas: Maryland, North Carolina, Virginia, the Washington, DC / Baltimore extended metropolitan area, and the full database (all three states and DC). The DC / Baltimore extended metropolitan area is comprised of 16 suburban counties around and between the two cities (but does not include the cities themselves).[2] The main reason for excluding the District of Columbia itself was the lack of data before 1985. Excluding the District allows estimating a model with a more complete time series extending back to 1970. The city of Washington, DC is included in regressions that include all three states together. These are referred to below and in the tables as the "all states" run.

*Base Model Results*

A summary of basic results for individual areas and all areas together is presented in Table 3. These are all estimated as ordinary least squares log-linear models with fixed effects.

The results across the five study areas are significant and fairly robust (i.e, consistent coefficients across region and specification). All specifications give statistically significant coefficients for the relationship between lane miles and VMT. The coefficient values range between about 0.3 and 0.6, which is consistent with other studies such as Noland (forthcoming). The DC / Baltimore metropolitan area specifications have the lowest values on the lane mile coefficient. This is a somewhat counterintuitive result since this area represents the most congested subset of the data. This area also has the largest use of alternative modes, such as transit, which would imply that road expansions could have a larger elasticity effect by drawing travelers from other modes. On the other hand, the lower coefficient could reflect a greater degree of infill development due to more mature land use patterns, relative to more rural counties. Population growth and per capita income coefficients are significant for

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[2] This area includes the Maryland counties of Anne Arundel, Baltimore, Calvert, Carroll, Charles, Frederick, Harford, Howard, Montgomery, and Prince George's. Virginia counties are Arlington, Fairfax, Fauquier, Loudon, Prince William, and Stafford. The City of Alexandria, Virginia is not included due to its jurisdictional definition as a city as opposed to a county.

the Washington DC / Baltimore metro area (the latter at a 90% level) but are not different in magnitude compared to overall results.

For the "all states" regressions, utilizing the full 3-state and DC database, the lane mile coefficient is slightly larger than for any of the individual study areas. A 10% change in lane miles correlates with about a 5.6% to 5.9% increase in travel. This could indicate that the cross-sectional variation in the data has a steeper slope than the variation within each state or more simply the result may be due to the shorter time series.

The coefficient on income per capita is more varied and much less significant across the models. The consistently strong significance for population is not especially surprising, since the number of people living in an area is expected to be a principal determinant of the level of vehicle travel in the area. The generally low value and low significance for income per capita suggests that in most areas, increases in income do not strongly correlate with increased vehicle travel (at least at the county level of analysis). This may also reflect the fact that, quite often, greater distances must be covered in rural areas, which also generally have lower income levels.

These results indicate that after controlling for population and income, a ten percent increase in lane miles correlates with a 3% percent to 6% increase in daily VMT in the mid-Atlantic region. Since these models do not include any lag structure, this result should be interpreted as an average response (i.e., combining short run and long run effects). The high t-statistics and low variation in results by area suggests that the results are quite robust. This is especially true considering the significant differences in the characteristics of the different study areas, as previously discussed.

Many unmeasured factors have contributed to VMT growth, including demographic changes over the last 40 years. One of the more commonly cited factors is the increased number of women in the workplace. Employment growth and growth in vehicle ownership are also drivers of VMT growth. However these variables are likely to be highly correlated with population growth and therefore cannot be directly included in the models. Models with total employment (by county), but excluding total population, were tested and gave essentially the same results as the models reported here. In any case, the use of a fixed effects approach controls for the variation in these unmeasured demographic factors both by county and over time.

*First Difference Model Results*

Specifications also were tested using a first difference model. The additive difference of the logs of variables (year t minus year t-1) were used, which captures percent changes through time, or the annual growth in the variables. This technique eliminates any problems of multi-collinearity which are present in the base model. Lane miles and population tend to be highly correlated in the levels model while Table 4 shows that the correlation between lane miles and population is virtually eliminated when differences are used. A summary of the first difference results is shown in Table 5.

The results of these regressions are somewhat more varied than the base runs, but still significant for lane miles in every study area (the Washington DC / Baltimore area is significant only at about the 90% confidence level). The coefficient for the change in population was insignificant in most areas. The "R-squared" values in these runs are quite low[3], although this is not uncommon for first difference runs, which tend to draw out the stochastic component of the change in variables from year to year.

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[3] "R-Squared" values, while similar, do not correspond to $R^2$ as calculated in OLS regressions. See StataCorp (1999) for a discussion of "R-Squared" as defined under the xtreg procedure.

The coefficient on lane miles varies from a low of 0.15 (for the Washington DC / Baltimore metropolitan area) to a maximum of 0.61 (for North Carolina). This range is slightly broader than, but not inconsistent with, the base run results. The lane mile coefficients for Virginia are similar to those for the Washington DC / Baltimore metropolitan area, and much lower than for Maryland and North Carolina. These latter two areas have a coefficient on population that is significant, which may explain the difference in the results for lane miles, and may indicate that growth in travel is more population-driven in these areas than in the other states.

*Simultaneity Bias and Testing for Causal Relationships*

One of the key issues of debate over the existence of induced travel is whether the generation of additional VMT on new or expanded roads merely reflects the response of planners to the forecast demand for travel, i.e. are planners merely accommodating travel increases that would occur in any case? The analysis presented above is likely to suffer from some degree of simultaneity bias if the causal relationship is reversed (that is, forecasts of VMT result in new road capacity). To assess this relationship and the magnitude of simultaneity bias we use two alternative methods. First, a Granger Causality test is used to test the time precedence of the relationship; that is, does lane mile growth precede VMT growth, or vice-versa? Second, we estimate an instrumental variable regression using two-stage least squares estimation to test whether lane miles are truly exogenous.

The long time series of data (30 years) for both Maryland and Virginia allow the use of a Granger Causality test. Maddala (1992**)** points out that the Granger test is not strictly a test for exogeneity, but rather for the time-precedence of the variables. The test is specified by including both a backward and a forward lag in the regression. If the backward lag is statistically significant while the forward lag is not, then this indicates that the independent variable temporally precedes the dependent variable (i.e., lane miles precede VMT). If the significance is reversed, then the dependent variable precedes the independent variable (i.e., VMT precedes lane miles).

Results for the Granger test are presented in Table 6. A difference model was used due to multicollinearity between the backward and forward lag variables when using a levels model. This is similar to the difference models shown in Table 5. Analysis of the data for Maryland and Virginia using a one year backward and forward lag and also a two year backward and forward lag are shown. The backward lag terms are statistically significant above the 95% level for three of the models but not for the 2 year lag for Maryland. In all cases the forward lag is not statistically significant.

This result suggests that lane mile growth precedes growth in VMT. However, as mentioned, this is not evidence of causality, i.e. that increases in lane miles *cause* increases in VMT, since the results can also be explained by planning that correctly anticipates future growth in VMT by building new capacity in advance.

The second and more powerful technique to correct for simultaneity bias is the use of an instrumental variable in a two stage least squares regression. A good instrument for lane miles is one that is correlated with lane miles but not correlated with VMT. It is common to use an instrument which is a lagged value of the variable of interest. Using the growth (or difference) model specified previously we "instrument" the growth in lane miles by using growth in lane miles over two and three year periods (that is $\log(LM_t) - \log(LM_{t-l})$, where $l = 2$ or 3). This variable is both highly correlated with the growth in lane miles and not correlated with the growth in VMT, as can be seen in Tables 7 – 10 for Maryland, Virginia, North Carolina, and the All States data.

Table 11 shows the results of four fixed effect regressions with growth in lane miles as the dependent variable. As can be seen, the growth in lane miles over a two year or a three year period is a highly significant predictor of growth in lane miles in the current year. Growth in per capita income is not a significant determinant of lane mile growth while population growth shows a negative sign and is only relatively strong for Maryland and Virginia.

Table 12 shows the results using the instrumental variable in a two stage least squares regression. These results should be compared with the coefficient estimates in the first difference model. The results generally show that the lane mile coefficient is both positive and significant at or above the 95% confidence level. The lane mile coefficients are generally similar in magnitude to the results shown in Table 5. Results for the "all states" model are 0.505 and 0.457 compared to 0.433 in the previous model. The coefficients for Maryland are slightly smaller, 0.397 and 0.290 compared to 0.527. North Carolina has coefficient values of 0.638 and 0.479 compared to 0.612 while the coefficient values for Virginia are higher when the instrument is used, 0.288 and 0.444 compared to 0.145. Overall these results appear to provide a strong indication that growth in lane miles is exogenous and therefore "causes" the growth in VMT, with lane mile elasticities ranging from about 0.2 to 0.6.

**Conclusions and Policy Implications**

The results presented indicate a significant relationship between the level of highway capacity, as measured by lane miles, and the level of travel, measured by daily VMT, in the mid-Atlantic region of the U.S. After accounting for other important determinants of travel and for potential simultaneity bias, the estimated elasticity between VMT and lane miles is estimated at between 0.2 to 0.6. This implies that a 10% increase in lane mileage can result in anywhere from a 2% to 6% increase in total VMT. A Granger test further indicates that changes in lane miles precede changes in travel.

Although there is some variation in the results across study area and specification, there is a considerable degree of consistency in both the significance and the value of the lane mile coefficient across all the models that were estimated. This is perhaps especially interesting given the significant differences in the geographic and population characteristics of the three states, as discussed above in the section on preliminary data analysis. It should be noted that the elasticity estimates do not account for potential long run impacts, such as ultimate changes in land use, that may generate further growth in VMT. On the other hand, the similar results in urban (DC/Baltimore) and mostly rural (e.g. North Carolina) areas suggest that both short-run congestion effects and longer run land use/growth effects may be important contributors to induced demand. While it is not possible to disentangle these effects with the data available, it is certainly suggestive that induced travel from new development (even in uncongested areas) may be significant.

These results add to a growing literature that appears to be unable to reject the induced travel hypotheses. The implications for those who advocate increased mobility should be reassuring, as the estimated relationship implies that adding roadway capacity reduces the cost of travel and encourages greater overall travel, and hence, mobility. On the other hand, if congestion reduction is of paramount concern, then induced travel implies that some or even most of the congestion reduction benefits of capacity expansion will be lost over time. Given a desire to both increase mobility and reduce congestion, the key policy question is whether individual demand for mobility is best served by increases in highway capacity or by alternative means, such as provision of alternative modes of travel, demand management policies or urban design changes. Environmental costs may also be more significant when induced travel impacts are accounted for, resulting in major differences in the relative social costs and benefits of alternative mobility enhancing projects.

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**Figure 1**

**Graphic Representation of the Impact of Roadway Expansion on Travel**

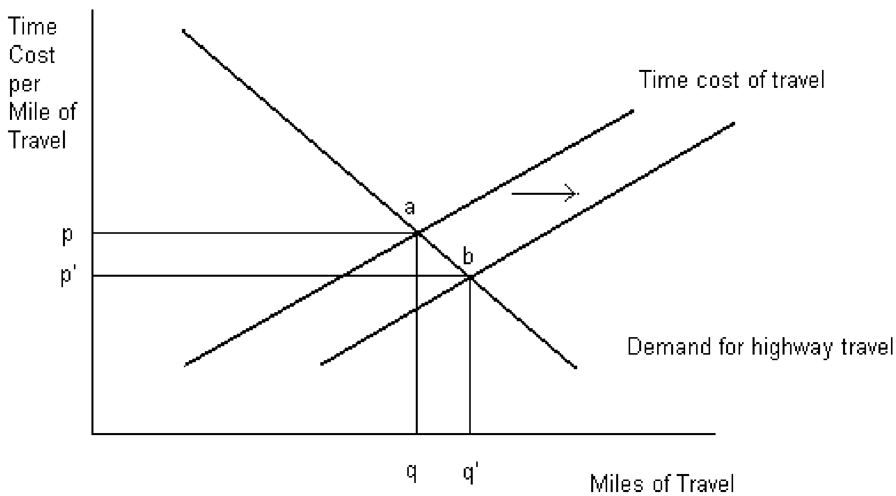

**Table 1**

**Average Values of Key County Variables in 1995**

| | *Units* | *Maryland* | *North Carolina* | *Virginia* | *Washington, DC/ Baltimore area* | *All* |
|---|---|---|---|---|---|---|
| Total # of Counties | x | 23 | 100 | 96 | 16 | 220 |
| Average Geographic Area | square miles | 421 | 487 | 399 | 417 | 440 |
| Average Population | people | 188,699 | 71,867 | 45,582 | 326,878 | 74,804 |
| Average Population Density | people/sq. mile | 422 | 148 | 194 | 1,155 | 237 |
| Average Daily VMT | miles/day | 3,536,397 | 1,297,601 | 1,064,583 | 5,834,860 | 1,457,690 |
| Average Daily VMT per Capita | VMT/person | 21.62 | 20.55 | 29.25 | 19.77 | 24.43 |
| Average Lane Miles | miles | 624.42 | 364.60 | 260.28 | 683.45 | 349.45 |
| Average Lane Miles per Capita | lane miles/person | 0.0072 | 0.0087 | 0.0117 | 0.0031 | 0.0098 |
| Average VMT per Lane Mile | VMT/lane mile | 4,357 | 3,055 | 3,475 | 8,224 | 3,392 |
| Average Income per Capita | 1998$ | 24,644 | 19,846 | 20,891 | 29,623 | 20,865 |
| Average Total # of Jobs | jobs | 101,128 | 43,705 | 31,481 | 149,293 | 47,508 |

**Table 2**

**Average Annual Growth Rates (by state and area based on years of available data)**

| | *Maryland* | *North Carolina* | *Virginia* | *Washington, DC/ Baltimore area* | *All* |
|---|---|---|---|---|---|
| Years of Data | 1969 - 1996 | 1984 - 1997 | 1970 - 1996 | 1970-1996 | 1985 - 1995 |
| Population | 1.72% | 0.96% | 1.32% | 2.66% | 1.10% |
| Population Density | 1.72% | 0.97% | 1.33% | 2.66% | 1.11% |
| VMT | 3.46% | 3.46% | 3.44% | 4.16% | 3.28% |
| Lane Miles | 0.38% | 0.58% | 0.61% | 0.87% | 0.45% |
| Population per Lane Mile | 1.34% | 0.38% | 0.71% | 1.78% | 0.65% |
| VMT per Lane Mile | 3.07% | 2.86% | 2.81% | 3.26% | 2.82% |
| Income per Capita | 1.50% | 1.74% | 1.87% | 1.76% | 1.42% |
| Jobs | 2.52% | 1.74% | 1.94% | 2.93% | 1.93% |

**Table 3**

**Base Model Results**

| Dependent Variable | LOG(VMT) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| State | *All States* | | *Maryland* | | *North Carolina* | | *Virginia* | | *Washington, DC – Baltimore metropolitan area* | |
| Years of Data | 1985-1995 | | 1969-1996 | | 1985-1997 | | 1970-1996 | | 1970-1996 | |
| Log (Lane Miles) | 0.587 | 0.564 | 0.451 | 0.451 | 0.475 | 0.435 | 0.506 | 0.508 | 0.331 | 0.327 |
| | (12.4) | (11.9) | (8.01) | (8.00) | (9.79) | (8.02) | (15.5) | (15.6) | (6.17) | (6.10) |
| Log (Population) | 0.520 | 0.569 | 0.659 | 0.655 | 0.560 | 0.585 | 0.507 | 0.504 | 0.518 | 0.502 |
| | (13.6) | (14.3) | (24.2) | (22.0) | (10.7) | (9.39) | (25.7) | (25.6) | (17.0) | (16.0) |
| Log (Income Per Capita) | - | 0.195 | - | 0.026 | - | 0.057 | - | 0.110 | - | 0.167 |
| | - | (4.18) | - | (0.369) | - | (0.958) | - | (3.25) | - | (1.87) |
| Constant | 4.51 | 2.21 | 3.38 | 3.19 | 4.85 | 4.24 | 4.90 | 3.89 | 6.09 | 5.27 |
| | (9.23) | (3.01) | (7.77) | (4.62) | (7.80) | (4.11) | (20.0) | (9.82) | (13.6) | (5.73) |
| N | 2420 | 2420 | 644 | 644 | 1300 | 1200 | 2592 | 2592 | 432 | 432 |
| “R-Squared” | 0.710 | 0.713 | 0.948 | 0.948 | 0.856 | 0.838 | 0.883 | 0.884 | 0.963 | 0.963 |

T-stats are in parentheses

County and time specific constants are omitted for brevity.

**Table 4**

**Correlation between Lane Miles and Population**

| | *Base Model* | *Difference Model* |
|---|---|---|
| All States | 0.816 | 0.040 |
| Maryland | 0.903 | 0.120 |
| North Carolina | 0.821 | 0.066 |
| Virginia | 0.686 | 0.077 |
| Washington, DC / Baltimore metropolitan area | 0.722 | 0.058 |

**Table 5**

**First Difference Model Results**

| Dependent Variable | LOG(VMT) Difference* | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| State | *All States* | | *Maryland* | | *North Carolina* | | *Virginia* | | *Washington, DC – Baltimore metropolitan area* | |
| Years of Data | 1985-1995 | | 1970-1996 | | 1986-1997 | | 1971-1996 | | 1971-1996 | |
| Log (Lane Miles Difference) | 0.434 | 0.433 | 0.517 | 0.527 | 0.609 | 0.612 | 0.149 | 0.145 | 0.153 | 0.154 |
| | (5.84) | (5.83) | (3.40) | (3.47) | (6.95) | (6.77) | (3.56) | (3.45) | (1.66) | (1.66) |
| Log (Population Difference) | 0.067 | 0.075 | 0.114 | 0.243 | 0.281 | 0.372 | 0.117 | 0.143 | 0.347 | 0.379 |
| | (0.485) | (0.535) | (0.423) | (0.877) | (0.989) | (1.17) | (2.21) | (2.67) | (1.88) | (1.92) |
| Log (Income Per Capita Difference) | - | 0.023 | - | 0.257 | - | 0.095 | - | 0.103 | - | 0.062 |
| | - | (0.334) | - | (2.03) | - | (1.02) | - | (2.73) | - | (0.454) |
| Constant | 0.006 | 0.005 | 0.058 | 0.057 | -0.020 | -0.027 | 0.034 | 0.031 | 0.068 | 0.064 |
| | (0.275) | (0.238) | (3.01) | (2.95) | (-0.874) | (-1.11) | (2.72) | (2.43) | (3.97) | (3.26) |
| N | 2200 | 2200 | 621 | 621 | 1200 | 1100 | 2496 | 2496 | 416 | 416 |
| "R-Squared" | 0.053 | 0.055 | 0.175 | 0.181 | 0.129 | 0.131 | 0.184 | 0.186 | 0.328 | 0.328 |

T-stats are in parentheses

County and time specific constants are omitted for brevity.

**Table 6**

**Results of Granger Test using Difference Model**

| Dependent Variable: LOG(VMT) Difference | | | | |
|---|---|---|---|---|
| State | *Maryland* | *Virginia* | *Maryland* | *Virginia* |
| Years of Data | 1970-1996 | 1971-1996 | 1970-1996 | 1971-1996 |
| Log (Lane Miles Difference) –backward lag one year | 0.545 | 0.143 | - | - |
| | (3.450) | (3.356) | - | - |
| Log (Lane Miles Difference) – forward lag one year | -0.097 | -0.039 | - | - |
| | (-0.613) | (-0.876) | - | - |
| Log (Lane Miles Difference) –backward lag two years | - | - | -0.057 | 0.123 |
| | - | - | (-0.345) | (2.814) |
| Log (Lane Miles Difference) – forward lag two years | - | - | 0.220 | -0.024 |
| | - | - | (1.166) | (-0.477) |
| Log (Population Difference) | 0.236 | 0.156 | 0.317 | 0.153 |
| | (0.829) | (2.838) | (1.010) | (2.436) |
| Log (Income Per Capita Difference) | 0.257 | 0.109 | 0.218 | 0.111 |
| | (1.981) | (2.861) | (1.547) | (2.751) |
| Constant | 0.009 | 0.038 | -0.006 | -0.030 |
| | (0.592) | (6.273) | (-0.376) | (-4.954) |
| N | 598 | 2400 | 552 | 2208 |
| "R-Squared" | 0.181 | 0.190 | 0.156 | 0.197 |

T-Stats are in parentheses

County and time specific constants are omitted for brevity.

**Table 7**

**Correlation coefficients: All States**

| *All States* | Growth in VMT | Growth in Lane Miles | Growth in Lane Miles over two years | Growth in Lane Miles over three years |
|---|---|---|---|---|
| Growth in VMT | 1.000 | | | |
| Growth in Lane Miles | 0.166 | 1.000 | | |
| Growth in Lane Miles over two years | 0.128 | 0.685 | 1.000 | |
| Growth in Lane Miles over three years | 0.113 | 0.580 | 0.840 | 1.000 |

**Table 8**

**Correlation coefficients: Maryland**

| *Maryland* | Growth in VMT | Growth in Lane Miles | Growth in Lane Miles over two years | Growth in Lane Miles over three years |
|---|---|---|---|---|
| Growth in VMT | 1.000 | | | |
| Growth in Lane Miles | 0.113 | 1.000 | | |
| Growth in Lane Miles over two years | 0.073 | 0.755 | 1.000 | |
| Growth in Lane Miles over three years | 0.090 | 0.615 | 0.868 | 1.000 |

**Table 9**

**Correlation coefficients: North Carolina**

| *North Carolina* | Growth in VMT | Growth in Lane Miles | Growth in Lane Miles over two years | Growth in Lane Miles over three years |
|---|---|---|---|---|
| Growth in VMT | 1.000 | | | |
| Growth in Lane Miles | 0.276 | 1.000 | | |
| Growth in Lane Miles over two years | 0.201 | 0.697 | 1.000 | |
| Growth in Lane Miles over three years | 0.136 | 0.594 | 0.860 | 1.000 |

**Table 10**

**Correlation coefficients: Virginia**

| *Virginia* | Growth in VMT | Growth in Lane Miles | Growth in Lane Miles over two years | Growth in Lane Miles over three years |
|---|---|---|---|---|
| Growth in VMT | 1.000 | | | |
| Growth in Lane Miles | 0.071 | 1.000 | | |
| Growth in Lane Miles over two years | 0.091 | 0.702 | 1.000 | |
| Growth in Lane Miles over three years | 0.100 | 0.589 | 0.821 | 1.000 |

**Table 11**

**Fixed Effects Regressions with Lane Mile Growth as Dependent Variable**

| Dependent Variable: Growth in Lane Miles | *All States* | | *Maryland* | | *North Carolina* | | *Virginia* | |
|---|---|---|---|---|---|---|---|---|
| Growth in Lane Miles over two years | 0.497 (36.698) | | 0.505 (28.203) | | 0.598 (34.353) | | 0.474 (44.251) | |
| Growth in Lane Miles over three years | | 0.310 (21.077) | | 0.280 (16.512) | | 0.413 (20.747) | | 0.296 (30.500) |
| Growth in Population | -0.025 (-0.706) | -0.047 (-1.118) | -0.081 (-1.576) | -0.149 (-2.445) | -0.068 (-0.810) | -0.098 (-0.876) | 0.024 (1.139) | -0.032 (-1.310) |
| Growth in per capita income | 0.001 (0.079) | 0.008 (0.378) | 0.007 (0.287) | -0.025 (-0.867) | -0.015 (-0.624) | 0.003 (0.107) | 0.025 (1.860) | 0.038 (2.556) |
| Constant | -0.002 (-1.650) | -0.000 (-0.277) | 0.002 (0.709) | 0.004 (1.313) | -0.005 (-2.205) | 0.000 (0.157) | -0.002 (-1.056) | -0.003 (-1.172) |
| N | 1980 | 1760 | 598 | 575 | 1000 | 900 | 2400 | 2304 |
| "R-Squared" | 0.441 | 0.232 | 0.622 | 0.377 | 0.576 | 0.362 | 0.478 | 0.321 |

T-stats are in parentheses

County and time specific constants are omitted for brevity.

**Table 12**

**Instrumental Variable Regressions (with fixed effects)**

| Dependent Variable: Growth in VMT | *All States* | | *Maryland* | | *North Carolina* | | *Virginia* | |
|---|---|---|---|---|---|---|---|---|
| | Instrument = growth in lane miles over two years | Instrument = growth in lane miles over three years | Instrument = growth in lane miles over two years | Instrument = growth in lane miles over three years | Instrument = growth in lane miles over two years | Instrument = growth in lane miles over three years | Instrument = growth in lane miles over two years | Instrument = growth in lane miles over three years |
| Growth in Lane Miles | 0.505<br>(4.823) | 0.457<br>(2.796) | 0.397<br>(1.972) | 0.290<br>(0.948) | 0.638<br>(6.491) | 0.479<br>(3.705) | 0.288<br>(4.405) | 0.444<br>(4.958) |
| Growth in Population | 0.031<br>(0.234) | 0.031<br>(0.214) | 0.251<br>(0.864) | 0.219<br>(0.726) | 0.166<br>(0.589) | 0.387<br>(1.293) | 0.120<br>(1.998) | 0.114<br>(1.694) |
| Growth in per capita income | 0.002<br>(0.037) | -0.028<br>(-0.372) | 0.255<br>(1.923) | 0.292<br>(2.047) | 0.114<br>(1.423) | 0.133<br>(1.573) | 0.088<br>(2.232) | 0.080<br>(1.959) |
| Constant | -0.003<br>(-0.148) | -0.004<br>(-0.176) | 0.009<br>(0.451) | 0.008<br>(0.396) | 0.038<br>(1.900) | 0.038<br>(1.824) | 0.040<br>(3.098) | 0.043<br>(3.222) |
| N | 1980 | 1760 | 598 | 575 | 1000 | 900 | 2400 | 2304 |
| Adjusted $R^2$ | 0.031 | 0.024 | 0.112 | 0.089 | 0.060 | 0.060 | 0.172 | 0.199 |

T-stats are in parentheses

County and time specific constants are omitted for brevity.